LIST OF CURRENT CLAIMS

1. (currently amended) A statistical facial feature extraction method, comprising:

a first procedure for creating a statistical face shape model based on a plurality of training face images, including:

an image selecting step, to select N training face images;

a feature labeling step, to respectively label feature points located in n different blocks of the training face images to define corresponding shape vectors of the training face images;

an aligning step, to align each shape vector with a reference shape vector to thus obtain aligned shape vectors; and

a statistical face shape model computing step, to use a principal component analysis (PCA) process to compute a plurality of principal components based on the aligned shape vectors to create a statistical face shape model, wherein the statistical face shape model represents the shape vectors by combining a plurality of projection coefficients, and the statistical face shape model computing step includes: computing a mean value of the feature points of the aligned shape vectors to define a mean shape vector $\bar{x}$, subtracting each aligned shape vector x_a by the mean shape vector $\bar{x}$ to form a matrix A, computing a covariance matrix C of the matrix A, and computing a plurality of principal components according to eigenvectors to form the statistical face shape model; and

a second procedure for extracting a plurality of facial features from a test face image, including:

a test face image selecting step, to select a test face image;

an initial guessing step, to guess initial positions of n test feature points located in the test face image, wherein the initial position of each test feature point is a mean value of the feature points of the aligned shape vectors;

a search range defining step, to define n search ranges in the test face image, based on the initial position of each test feature point, wherein each search range corresponds to a different block;

a candidate feature point labeling step, to label a plurality of candidate feature points for each search range;

a test shape vector forming step, to do combination of the candidate feature points in different search ranges in order to form a plurality of test shape vectors; and

a determining step, to match the test shape vectors respectively to both the mean value and the principal components for computing a similarity, and to accordingly assign one feature point corresponding to one, having the best similarity, of the test shape vectors as facial features of the test face image.

2. (original) The method as claimed in claim 1, wherein in the feature labeling step of the first procedure, the feature points are coordinates for corners of eyes and mouth on each training face image.

3. (original) The method as claimed in claim 1, wherein the feature labeling step of the first procedure manually labels the feature points of each training face image.

4. (original) The method as claimed in claim 1, wherein the reference shape vector is one of the shape vectors.

5. (original) The method as claimed in claim 1, wherein the aligning step of the first procedure uses a 2D scaled rigid transform algorithm to align each shape vector with the reference shape vector.

6. (original) The method as claimed in claim 5, wherein the aligning step of the first procedure further comprises the steps of:

selecting the reference shape vector as $x_i = (x_{i1}, y_{i1}, \ldots, x_{in}, y_{in})$ and one of the shape vectors as $x_j = (x_{j1}, y_{j1}, \ldots, x_{jn}, y_{jn})$;

computing a squared Euclidean distance E between the vectors x_i and x_j based on the following equation $E = (x_i - M^{(N)}(\alpha,\theta)[x_j] - t)^T (x_i - M^{(N)}(\alpha,\theta)[x_j] - t)$, where $M^{(N)}(\alpha,\theta)[x_j] - t$ is a geometric transform function defining with a plurality of transfer parameters to align the vector x_j, the transfer parameters include a rotating angle θ, a scaling factor α, and a shifting vector represented by $t = (t_x, t_y)$, and $M^{(N)}(\alpha,\theta)$ is a 2n×2n diagonal blocked matrix as well as

$$M(\alpha,\theta)\begin{bmatrix} x_{jk} \\ y_{jk} \end{bmatrix} = \begin{pmatrix} \alpha\cos\theta x_{jk} - \alpha\sin\theta y_{jk} \\ \alpha\sin\theta x_{jk} + \alpha\cos\theta y_{jk} \end{pmatrix} \text{ for } 1 \leqq k \leqq n, \text{ as}$$

$$M(\alpha,\theta) = \begin{pmatrix} \alpha\cos\theta & -\alpha\sin\theta \\ \alpha\sin\theta & \alpha\cos\theta \end{pmatrix};$$

finding the smallest squared Euclidean distance and corresponding rotating angle θ_j, scaling factor α_j and shifting vector represented by $t_j = (t_{xj}, t_{yj})$ to align the shape vector x_j so similar as the reference shape vector x_i;

computing a sum of smallest squared Euclidean distances after the N shape vectors are all aligned so similar as the reference shape vector, ending the aligning step when the sum is smaller than a predetermined threshold;

computing a mean value of the feature points in each block for the aligned shape vectors to define a mean shape vector for each aligned shape vector as $\bar{x} = \frac{1}{N}\sum_{a=1}^{N} x_a$, wherein x_a is the aligned shape vector; and

assigning the mean shape vector as the reference shape vector and the aligned shape vectors as the shape vectors and then repeating the aligning step until all shape vectors are aligned.

7. (original) The method as claimed in claim 6, wherein the transfer parameters is obtained by a least square algorithm.

8. (original) The method as claimed in claim 1, wherein the statistical face shape model is a point distribution model (PDM).

9. (currently amended) The method as claimed in claim [[8]]1, wherein in the statistical face shape model computing step, the mean shape vector $\bar{x}$ is defined as $\bar{x} = \frac{1}{N}\sum_{a=1}^{N} x_a$, where xa is the aligned shape vector; the matrix A is formed as $A = \lfloor d_{x_1}, d_{x_2}, \ldots, d_{x_N} \rfloor$, where $d_{x_a} = x_a - \bar{x}$; the covariance matrix C is formed as $C = AA^T$; the eigenvectors are derived from $Cv_k^s = \lambda_k^s v_k^s$ with eigenvalues corresponding to the covariance matrix C, where λ_k^s represents eigenvalues of the covariance matrix C, v_k^s represents eigenvectors of the covariance matrix C, and 1≦ k≦ m, m being the dimension of the covariance matrix C for $\lambda_1^s \geq \lambda_2^s \geq \ldots \geq \lambda_m^s$ ~~the statistical face shape model computing step of the first procedure further comprises the steps of:~~

~~computing a mean value of the feature points of the aligned shape vectors to define a mean shape vector as~~ $\cancel{\bar{x} = \frac{1}{N}\sum_{a=1}^{N} x_a}$ ~~, wherein xa is the aligned shape vector;~~

~~subtracting each aligned shape vector by the mean shape vector to form a matrix as~~ $\cancel{A = \lfloor d_{x_1}, d_{x_2}, \ldots, d_{x_N} \rfloor}$~~, wherein~~ $\cancel{d_{x_a} = x_a - \bar{x}}$~~;~~

~~computing a covariance matrix of the matrix A as~~ $\cancel{C = AA^T}$~~; and~~

~~computing a plurality of principal components according to eigenvectors derived from~~ $\cancel{Cv_k^s = \lambda_k^s v_k^s}$ ~~with eigenvalues corresponding to the covariance matrix C, to form the statistical face shape model, wherein~~ $\cancel{\lambda_k^s}$ ~~represents eigenvalues of the covariance~~

~~matrix C, v_k^s represents eigenvectors of the covariance matrix C, and $1 \leqq k \leqq m$, where m is the dimension of the covariance matrix C for $\lambda_1^s \geq \lambda_2^s \geq \ldots \geq \lambda_m^s$.~~

10. (original) The method as claimed in claim 1, wherein each shape vector x_j consists of n feature vectors s_j located in different blocks, so an average value as $t = \frac{1}{N}\sum_{j=1}^{N} s_j$ of the feature vectors s_j corresponding to special blocks of all shape vectors x_j is defined as a feature template.

11. (original) The method as claimed in claim 1, wherein in the initial guessing step of the second procedure, scaling of initial guess shapes formed by the test feature points is aligned so similar as the test face image.

12. (original) The method as claimed in claim 10, wherein the candidate feature point labeling step of the second procedure further comprises the steps of:

labeling a plurality of reference points derived from $I_i \cong t + \sum_{j=1}^{k} b_j p_j$ respectively in each search range, where t is the feature template of block corresponding to a search range, p_j is j-th principal component of the statistical face shape model computed from the training feature vectors, and b_j is an associated projection coefficient;

using $\varepsilon = \| I_i - t - \sum_{j=1}^{k} b_j p_j \|_2$ to compute an error value between one of the reference points and the corresponding principal component p_j and projection coefficient b_j; and

selecting preceding k smallest error values and defining the k smallest error values as feature points of the search range.

13. (original) The method as claimed in claim 12, wherein the test shape vector forming step of the second procedure does combination of the candidate feature points in different search ranges to thus form k^n test shape vectors.

14. (original) The method as claimed in claim 10, wherein the determining step of the second procedure further comprises the steps of:

using the average value of the aligned shape vectors and the principal components of the statistical face shape model to represent an approximate value of the test shape vector as $x \cong \bar{x} + \sum_{j=1}^{k} b_j^x p_j^x$, where $\bar{x}$ is a mean shape vector defined according to the mean value of the feature points of the aligned shape vectors, p_j^x is j-th principal component of the statistical face shape model, and b_j^x is a corresponding projection coefficient;

using a 2D scaled rigid transform algorithm to align the test shape vector represented by $x \cong M(\alpha,\theta)\left[\bar{x} + \sum_{j=1}^{k} b_j^x p_j^x\right] + t$, where θ, α and t are a rotating angle, a scaling factor and a shifting vector respectively;

computing a normalized distance of the aligned test shape vectors by $d(x) = \sqrt{\sum_{j=1}^{k}\left(\frac{b_j^x}{\lambda_j^x}\right)^2}$; and

assigning one candidate feature point corresponding to one, having the smallest normalized distance, of the aligned test shape vectors as facial feature of the test face image.

15. (original) The method as claimed in claim 10, wherein the determining step of the second procedure further comprises the steps of:

using the average value of the aligned shape vectors and the principal components of the statistical face shape model to represent an approximate value of the test shape

vector as $x \cong \bar{x} + \sum_{j=1}^{k} b_j^x p_j^x$, where $\bar{x}$ is a mean shape vector defined according to the mean value of the feature points of the aligned shape vectors, p_j^x is j-th principal component of the statistical face shape model, and b_j^x is a corresponding projection coefficient;

using a 2D scaled rigid transform algorithm to align the test shape vector represented by $x \cong M(\alpha,\theta)\left[\bar{x} + \sum_{j=1}^{k} b_j^x p_j^x\right] + t$, where θ, α and t are a rotating angle, a scaling factor and a shifting vector respectively;

computing an error value between the test shape vector and the average value of the aligned test shape vectors by $\varepsilon(x) = w_1 \sum_{i=1}^{n} \| I_i(x) - t_i - \sum_{j=1}^{k} b_j^i p_j^i \|_2 + w_2 d(x)$, where $\sum_{i=1}^{n} \| I_i(x) - t_i - \sum_{j=1}^{k} b_j^i p_j^i \|_2$ is a similarity of the test shape vector to corresponding aligned shape vector x_a, and d(x) is the normalized distance of the aligned test shape vectors; and

assigning one candidate feature point corresponding to one, having the smallest error value, of the test shape vectors as facial feature of the test face image.

16. (original) The method as claimed in claim 15, wherein the error value is computed by an equation $\varepsilon(x) = w_1 \left(\sum_{i=1}^{n} \sqrt{\sum_{j=1}^{k} \left(\frac{b_j^i}{\lambda_j^i} \right)^2} \right) + w_2 d(x)$.